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PERFORMANCE EVALUATION OF SPATIAL FILTERS USING FULL-REFERENCE IMAGE QUALITY METRICS

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ABSTRACT

The de-noising of digital images is crucial preprocessing step before moving toward image segmentation, representation and object recognition. It is important to find out efficacy of filter for different noise models because filtering operation is application oriented task and performance varies according to type of noise present in images. A comparative study has made to elucidate the behavior of different spatial filtering techniques under different noise models. In this paper different types of noises like Gaussian noise, Speckle noise, Salt & Pepper noise are applied on grayscale standard image of Lenna and using spatial filtering techniques the values of full reference based image quality metrics are found and compared in tabular and graphical form. The outcome of comparative study shows that Lee, Kuan and Anisotropic Diffusion Filter worked well for Speckle noise, the Salt and Pepper noise has significantly reduced using Median and AWMF, and the Mean filter and Wiener filter works immensely efficient for reducing Gaussian noise.

Keywords: spatial filter, additive noise, multiplicative noise, image quality metrics.

INTRODUCTION

The use of digital images is rapidly increasing in the field of education, medical diagnosis, astronomy, and manufacturing industry. There are numerous other areas in which digital images are being used. The problems associated with digital images are emerging with the increase in its application. The degradations in digital images are mainly classified by [1] as given below:

- Degradation due to non zero dimensions of picture element used in device used for imaging, which is known as spatial degradation.
- Degradation due to non zero exposure time of photosensitive material used in device used for imaging, which is known as temporal degradation.
- Degradation due to distortion of image geometry, which is known as geometrical degradations.
- Degradation due to modification in gray level of image element, which is known as noise.

Our main focus in this paper will be on degradation due to modification of gray level i.e., noise. The Number of problems in digital images can arises due to noise because the noise damages the important features of the image. Noise may occur in digital image during acquisition, transmission and retrieval process, and degrades the quality of image. The purpose of de-noising is to eliminate noise while preserving edges and other sharp transitions [2]. The removal of noise is still a difficult task for researchers because de- noising algorithms may cause blurring of edges and it may eliminate some important features of image also. The algorithm selected for de-noising depends upon the nature of the noise present in the image and the type of image to be de-noised because the de-noising algorithm used for ultrasound images may not be suitable for satellite images. Similarly the de-noising algorithm used for Gaussian noise may not be suitable for speckle noise. The de-noising is a process of restoring an image into accurate state and for this it must be known by which noise model the image has been degraded. When a degradation model is known the inverse process can be applied to restore an image back into original form. The image degradation and restoration model [2] is given as follows.

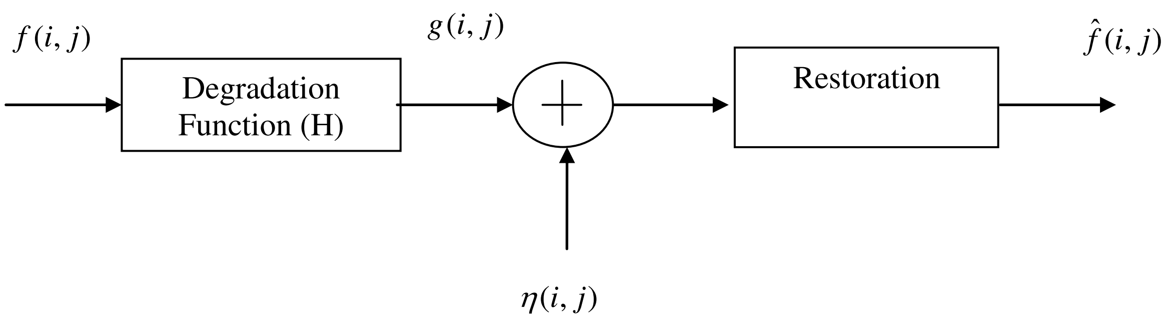

Figure-1. Image restoration/degradation model.

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Where $f(i, j)$ is the original image, $g(i, j)$ is noisy image corrupted by some known degradation and additive noise $\eta(i, j)$ and $\hat{f}(i, j)$ restored image which is approximation of original image. In this paper degradation function is assumed to be identity and filtering methods will be based on noise present in the image. The noise present is assumed to be independent so there is no correlation between pixel value and noise. The spatial filtering methods Mean, Median, Adaptive Weighted Median Filter(AWMF), Wiener, Kuan, Frost and Anisotropic Diffusion filter are applied on standard image of Lenna corrupted with Gaussian noise, Speckle noise and Salt & Pepper noise respectively. The efficacy of different spatial filter has evaluated using full reference image quality metrics Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR), Structural Content (SC), Average Difference (AD), Maximum Difference (MD), Normalized Correlation Coefficient (NCC), Normalized Absolute Error (NAE), Laplacian Mean Square Error (LMSE) and Structural Similarity Index (SSIM).

NOISE MODELS

Image noise is unwanted signal present in captured image. Images are corrupted by noise during the process of acquisition, storing and transmission, like speckle noise is inherited in coherent imaging and occurs during image acquisition. Ultrasound, synthetic aperture radar imaging are examples of coherent imaging [4]. During transmission the noise mainly occurs in analogue channels. The digital channels restrict the interference of artifacts with signal over transmission channel. The noise visually degrades the quality of image as well as make difficult to study area of interest. In this section, various noise models, their categorizations and their probability distributed function will be discussed. The noise is generally categorized as additive or multiplicative [3]. The Gaussian noise is additive in nature. It is represented as in following equation (1).

$$g(i, j) = f(i, j) + \eta(i, j) \tag{1}$$

The value of each pixel in the image having Gaussian noise will be sum of the value of pixel in reference image and the value of random Gaussian distributed noise. This type of noise has a bell shaped, and The Gaussian probability distribution function is given as follow in equation (2).

$$P(z) = \frac{1}{\sigma\sqrt{2\Pi}} e^{\frac{-(z-\mu)^2}{2\sigma^2}} \tag{2}$$

Where μ represents mean intensity of given image, z represents the gray level and σ is the standard deviation of noise. The probability distribution function of Gaussian noise and Gaussian noise pattern generated in matlab is given in following Figure-2.

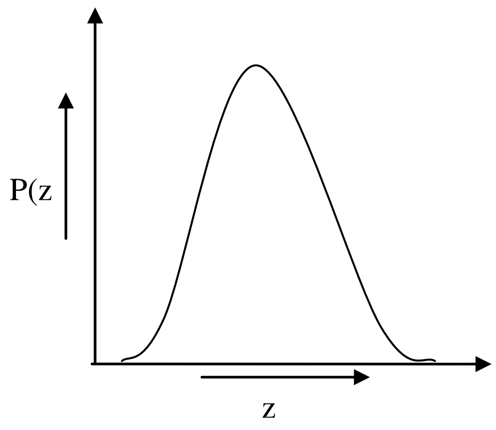

Figure-2. Distribution function for Gaussian Noise.

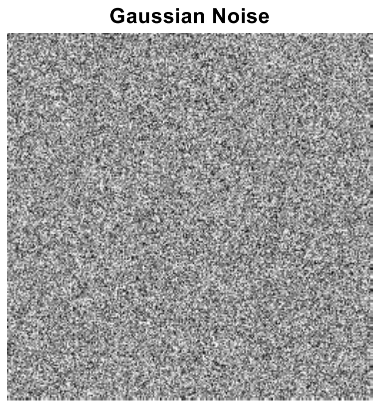

Figure-3. Gaussian noise pattern generated in Matlab.

The Speckle noise which is multiplicative in nature emerges when coherent light illuminates the rough surface then the reflected waves from the surface contains contribution of many independent scattering areas [4]. The scattered components with relative delay of few wavelengths sums together while propagating to distant observation point and form a granular pattern and that pattern is termed as speckle. The speckle noise is intrinsic artifact of ultrasound and synthetic aperture radar imaging [5, 6]. The quality of the image can be improved by using speckle reduction filtering techniques. The speckle noise is multiplicative in nature and given in following equation

$$g(i, j) = f(i, j) * m(i, j) + n(i, j) \tag{3}$$

Where $f(i, j)$ is the original image, $g(i, j)$ is degraded image corrupted by additive noise $\eta(i, j)$ and multiplicative noise $m(i, j)$. Suppose the effect of additive noise such as sensor noise is negligible as compared to multiplicative noise.

$$n(i, j) << m(i, j) \tag{4}$$

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equation (1) can be rewritten as

$$g(i, j) = f(i, j) * m(i, j) \tag{5}$$

The logarithmic process converts the given multiplicative equation into additive form. The probability density function for speckle noise is given below.

$$P(z) = \frac{z^{\alpha - 1}}{(\alpha - 1)!\,a^{\alpha}} e^{-z/a} \tag{6}$$

Where z represents the gray level and variance is a^{α}. The speckle pattern can be of three types [5] a) Fully formed speckle, b) Non randomly distributed with long range order, and c) Non randomly distributed with short range order. This classification is according to scatterer number density and spatial distribution. The probability density function of Speckle noise and pattern of speckle noise generated in matlab is given in following Figure.

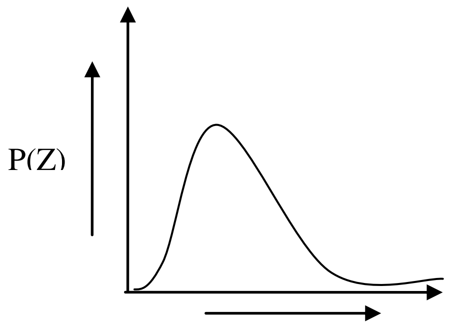

Figure-4. Distribution function for Speckle Noise.

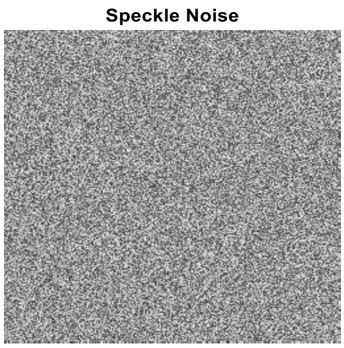

Figure-5. Gaussian noise pattern generated in Matlab.

The salt and pepper noise is basically an impulse noise which is caused by sudden and sharp disturbances in camera sensors or transmission in noisy channels [8]. The other type of impulse noise is random valued noise. The pixel values in image corrupted with salt and pepper noise are set to either value 'm' or 'n' and the pixels which are unaffected remain unchanged. The values 'm' and 'n' are minimum and maximum value within dynamic range. For an 8 bit image having 256 gray values, the value of salt noise is set to 255 and value of pepper noise is set to 0. The probability density function P(z) for salt &pepper noise is given as follow:

$$P(z) = \begin{cases} P_m & \text{for} \quad z = m \\ P_n & \text{for} \quad z = n \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Where 'z' represents the gray level. Once the median was the most efficient and effective filter for removing salt and pepper noise. But the median filter cause blurring of edges and can introduce artifacts when noise level increase beyond threshold value [8]. In order to avoid these problems alternatives based on median filter like 'adaptive' or 'switching' filters were proposed which we will discuss in next section. The graphical representation of probability density function of salt and pepper noise and pattern of salt and pepper noise generated in matlab is given as follow:

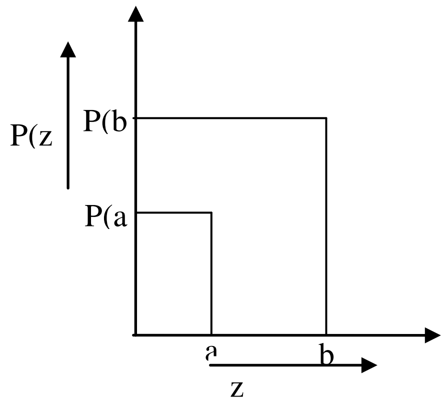

Figure-6. Distribution function for salt and pepper Noise.

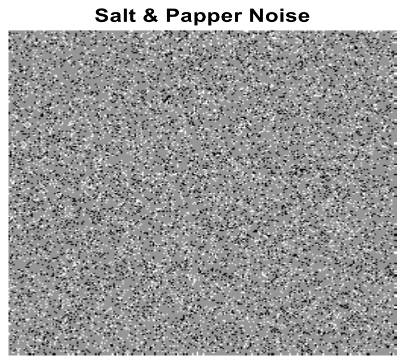

Figure-7. Gaussian noise pattern generated in Matlab.

FILTERING OF DIGITAL IMAGES

Noise may arise in digital images due to number of factors like improper sensing element, improper lightning conditions, or environment factors etc. The de-noising of images is very important pre-processing step in order to get good results in segmentation, object recognition and representation. For example, the

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ultrasound images contain speckle noise during acquisition which is undesirable because as it affects the task of human interpretation and diagnosis.But removal of noise from digital images may introduce some artifacts and may also cause blurring due to which area of interest in digital image may damage. Along with de-noising, it is very important to preserve edges and important characteristics of image.

A classification of linear and non linear filters can be made in spatial filtering [9]. The value of output pixel in linear filtering is the linear combination of the values of the pixels in the neighborhood of input pixel, whereas output is not a linear function of input in case of linear filtering. A Significant work in spatial filtering has done by [10] using mean filter which is based on local statistical measures. The wiener filter [11] is considered as a best filter among the class of linear spatial filters. The Gaussian noise can be significantly reduced using wiener filter. In [12] Pratt also made a qualitative study of two dimensional median filters of different size and shapes. They concluded that the irrespective of size and shape of window the median filter works well for suppressing salt and pepper noise. The median filter belongs to a class of non linear spatial filters. For reducing speckle noise, L_2 –mean filter [13], Adaptive weighted median filter [14] and filter based on non linear diffusion [15] belongs to post formation filtering methods which works directly on original image were best. In [16] new adaptive filtering algorithm was used in which arithmetic filter was used for homogenous regions and median filter was used for edge pixels. In[23] 1990, perona and malik proposed a novel filtering using anisotropic diffusion based on the filters proposed by Lee [20], Frost [21] and Kuan [22].These filters are based on minimizing mean square error. The use of non linear PDE methods involving anisotropic diffusion has significantly increased. In [22] noise smoothing adapts according to changes in non-stationary local mean and non-stationary local variance. In this paper efficacy of some of the existing filtering techniques like Mean, Median, AWMF, Lee, Kuan, Frost and Anisotropic diffusion filter has compared using full reference objective image quality metrics.

Mean filter

The mean filter is used to reduce intensity variation between pixels by providing smoothness in the given digital image. The intensity variation is suppressed but blurring of edges and introduction of artifacts may occur in image filtered by mean filter. It is an average filtering technique which means a mask is applied over each pixel and pixel value is replaced by average of all neighboring pixels value [11].

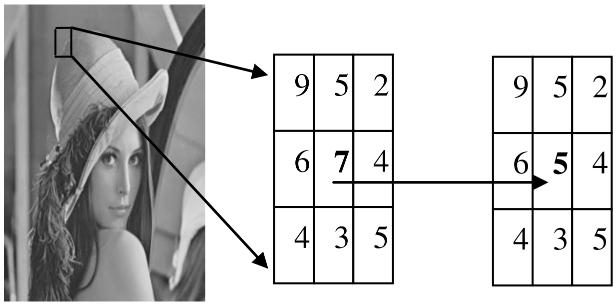

Figure-8. An example of Mean Filter.

Mask size begins with 3 and may increase up to finite limit but as mask size increases the blurring may also increase. The problem with mean filter is that sometimes a single pixel with extreme value significantly affects its neighbor pixels. The mean filter is given as follow:

$$\hat{f}(i,j) = \frac{1}{mn}\sum_{(x,y)\in S_{i,j}} g(x,y) \quad (8)$$

Where $\hat{f}(i,j)$ is de-noised image, $g(i,j)$ is degraded image and $S_{i,j}$ is the area defined by mxn size mask.

Median filter

Median filter is the order-statistical filter which works well for salt and pepper noise but not suitable for Gaussian and speckle noise. The value of pixel (i,j) in filtered image will be median of all values given in neighborhood of (i,j) in original image. The neighborhood window may be the size of 3x3, 5x5, 7x7 etc. The size of window will always be in odd numbers. The window selected is moved to entire image in the same way to mean filter. It also preserves the details and does not introduce artifacts in the digital image while de-noising unlike linear filters such as mean filter which may blur the edges [11,12]. The reason is median filter is not much sensitive to extreme values unlike mean filter. It belongs to the category of non-linear filters. The median filter is defined as follow:

$$\hat{f}(i,j) = \frac{median}{(x,y)\in w_{i,j}}\left(f(x,y)\right) \quad (9)$$

Where $f(i,j)$ is the reference image, $\hat{f}(i,j)$ is de-noised image, (i,j) is the pixel in $f(i,j)$ to be processed and $f(x,y)$ is local window. It is easy implement and easy to formulate. The algorithm for median filter is given as

Step 1: Consider each pixel in the image and select 3x3 size neighborhood.

Step 2: Sort all the pixels in given neighborhood into numerical order.

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Step 3: Find out median value.
Step 4: Replace the given pixel with calculated median value.
Step 5: Repeat all above steps until all the pixels in the given image are replaced with median values.

Adaptive weighted median filter

The adaptive median filter works on the principle that the behavior of filter applied is changes when statistical measures like mean, variance changes within image. It also changes size of neighborhood window during execution. The basic principle of algorithm remain same that we need to find median with in neighborhood window but value of given pixel will be replace with median or not, it depends upon statistical measures [17]. The algorithm for adaptive median filter is given as follow:

Step 1: Select initial window_size and maximum_window_size.
Step 2: Consider next pixel of image and repeat following steps for each and every pixel of image.
Step 3: Find out Min_value, Max_value and Median_value within given neighborhood.
Step 4: If Min_value<Median_value<Max_value
If Min_value<Pixel_value<Max_value
then return Pixel_value and goto step-2
else return Median_value and goto step-2
else
ifwindow_size<maximum_window_size
then increase size of neighborhood window
andgoto step-4
else return pixel_value and goto step-2

The Min_value and Max_value are minimum and maximum intensity values, generally considered as component of impulse noise. We start with finding Median_value and if it fall between Max_value and Min_value and If pixel value does not falls between Max_value and Min_value then it is considered as noise and get replaced with median value of neighborhood window, otherwise the pixel value will remain unaltered. but if median value itself is extreme then window size is increased and algorithm restart from beginning [17]. It works well for impulse noise but does not give good results for speckle and Gaussian noise.

Wiener filter

The Wiener Filter belongs to a class of optimum stationary linear filter to filter images degraded by additive noise. There is a need to take assumption in wiener filter that signal and noise are second order stationary and performance criteria is to find filtered image such that Mean square error between degraded image and filtered image is minimum [18]. It can also be used in frequency domain as well as spatial domain. In frequency domain it is used for de-noising and de-blurring whereas in spatial domain only de-noising purpose is solved [19]. The spatial domain is taken as a base of wiener filtering in this paper. It uses both local statistics and global statistics for de-noising. For a given degraded image g(i,j), the wiener filter is given as follow:

$$\hat{f}(i,j) = \bar{\mu} + \frac{\sigma_f^2}{\sigma_f^2 + \sigma_n^2}\left(g(i,j) - \bar{\mu}\right) \tag{10}$$

Where $\hat{f}(i,j)$ is de-noised image, $\breve{\mu}$ is local mean intensity, σ_f^2 is local variance, and σ_n^2 is variance of reference image. It is adaptively applied to noisy image which means it perform less smoothing for large variance and more smoothing for more smoothing for small variance.

Lee filter

The Lee Filter [20] is based on local statistical measure for de-noising and for preserving edges and fine details. It is an adaptive filter which means it performs filtering if variance over an area is high otherwise filtering operation will ignored. It works well for both additive and multiplicative noise although it was designed to reduce speckle noise. Initially mean and variance of each pixel is derived from its local mean and variance then the estimator which minimizes the mean square error is applied to get the de-noising algorithm. The Mathematical formula for Lee filter is given as follow:

$$\hat{f}(i,j) = W(i,j)\left[g(i,j) - \bar{\mu}\right] + \bar{\mu} \tag{11}$$

Where $W(i,j) = 1 - \frac{\sigma_n^2}{\sigma_g^2}$ when $\sigma_g^2 > \sigma_n^2$ and $W(i,j) = 0$ when $\sigma_n^2 > \sigma_g^2$. We know that σ_n^2 is variance of noisy image and σ_g^2 is variance of de-noised image. The range of W(i,j) lies between 0 and 1.

Frost filter

In [21] a de-noising model for radar image was developed for radar images which were corrupted by multiplicative noise. Ultrasound images and SAR images are usually corrupted by multiplicative noise and standard spatial filtering techniques do not work for multiplicative speckle noise. A model for de-noising was presented to minimize mean square error for smoothing Radar images. Due to non-coherent behavior the Radar images contains multiplicative noise and standard de-noising techniques are not applicable on it. The filter is applied on spatial domain and computationally it is very economical. It is an adaptive wiener filter which convolves the pixel value within a fixed size mask. The exponential impulse response k is given as:

$$k = \exp\left[-MC_y(i,j)|t|\right] \tag{12}$$

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Where M is filter parameter, and $|t_0|$ is distance measured from processed pixel (i,j). The filter is developed with assumption that both noise and signal are stationary. For radar images, the noise can be modeled as stationary but on a global basis the radar images are non-stationary [21]. Therefore the filter is adapted to the changes in local properties.

Kuan filter

In[22] the de-noising of digital images from signal dependent noise is done by using filter for noise smoothing which adapts according to changes in non-stationary local mean and local variance. The filter behave likes a point processor while smoothing uncorrelated, signal dependent noise but for multiplicative noise the filter behave like lee filter with some modification which permits various estimators for local variance of image. It is similar to Lee filter with more accuracy in de-noising and edge preservation because little or no approximation is required in total derivation. The formula for kuan filter is same as that of lee filter which is given in equation (11) but value of W(i,j) is changed and given as follow:

$$W(i,j) = 1 - \frac{\sigma_n^2 / \sigma_g^2}{1+\sigma_n^2} \tag{13}$$

Where σ_n^2 is the variance of noisy image and σ_g^2 is variance of de-noised image.

Anisotropic diffusion filter

Anisotropic Diffusion filter uses the concept of partial differential equation to reduce noise from digital image. Idea of modeling a filter for reducing speckle noise based on diffusion filter were first proposed by perona and malik in [23], they developed model of Speckle reducing anisotropic diffusion(SRAD). It can reduce speckle noise and preserve as well as enhance edges using anisotropic diffusion which was not possible with standard spatial filtering methods [24]. It is iterative procedure in which images are considered to consist of sub regions and diffusion filter works for smoothening within the region. It provides notable refinement in noise reduction and preservation of edges when compared with standard lee, kuan, and frost filters. The work later on extended by weickert in [15] and proposed the coherence enhancing diffusion based on tensor valued diffusion filter for smoothing. The Partial differential equation proposed by perona and malik for discrete domain is given as follow

$$I_{i,j}^{t+\Delta t} = I_{i,j}^{t+\Delta t} + \frac{\Delta t}{\left|S_{i,j}\right|} \sum_{p \in S_{i,j}} c\left(\nabla I_{(i,j),p}^{t}\right) \nabla I_{(i,j),p}^{t} \tag{14}$$

Where $I_{i,j}^t$ is the digital image, (i,j) denotes pixel position in 2 dimensional grid , Δt is the step size and $S_{i,j}$ is the spatial neighborhood of pixel (i,j). The edge preservation and smoothing within the region is the main advantage of anisotropic diffusion. The adaptive filtering approach and PDE later combined to derive speckle reducing anisotropic diffusion.

Image quality metrics

The quality of image can be judged on various parameters. The applications in which the human eye is the ultimate observer the subjective quality measures are used but there are some applications in which assessment of image quality should be made automatically on the basis of automated measures without any human involvement. The subjective metrics are categorized as single stimulus in which subject evaluates the quality of test image without any reference or source image and double stimulus in which test images are evaluated in the presence of source images [26]. The evaluation can be made from single to multiple repetitions. The results of subjective metrics can be interpreted on few scales, like average, good, best, below average, poor etc.

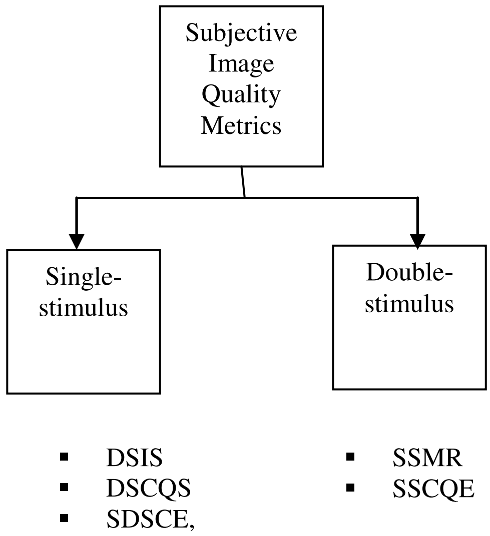

Figure-9. The subjective image quality metrics.

The objective image quality metrics can automatically predict the quality of image using some automated models without any human assistance. The aim of image quality is to improve overall appearance of image. Moreover it can also be used for following applications [24, 25].

- It can be used to standardize an image or algorithm for enhancement, compression or restoration.
- It can be used to keep check on quality of image.
- It can be used to optimize the given algorithm.

The objective image quality metrics can be further classified as Full-reference, Reduced-reference and No-reference.

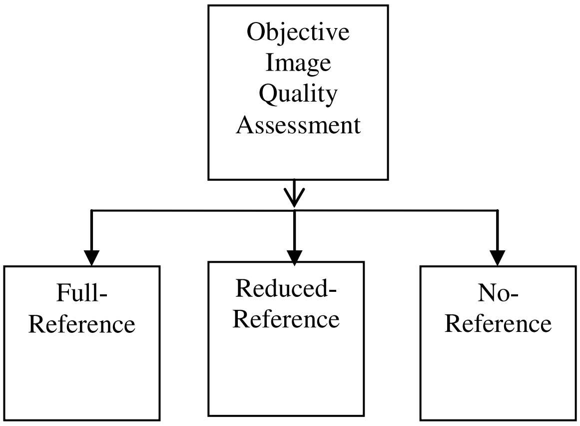

Figure-10. The objective image quality metrics.

In Full reference approach the quality of test image is compared with reference image. So reference image in this technique is assumed to be known. In some cases the reference image may not be available then we can use "No-Reference or Blind" method as Image quality metric. When reference image is partially available then Reduced- reference methods are used [28]. The study in this paper is made on Full-reference image quality metrics. In this paper we have considered $f(i,j)$ as a reference image, $\hat{f}(i,j)$ as a filtered image and M*N as a size of image.

Root mean square error

The mean square error is the sum of the square of difference between de-noised image and reference image intensity divided by size of image. A higher value of mean square error means the difference between de-noised image and reference image is large or image has not been de-noised [27]. Mathematically mean square error is defined as follow:

$$\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(\hat{f}(i,j)-f(i,j))^2 \tag{15}$$

The major drawback of MSE is its dependence on intensity scaling. The root mean square can be simply found by taking square root of the value of mean square error.

Peak Signal to Noise Ratio (PSNR)

The quality of image is measured as a ratio of maximum intensity available (Power in case of signal) to the square root of mean square error [27]. It is measured in decibels. For a given image f(i,j), the PSNR is mathematically defined as follow:

$$10\log\frac{S^2}{MSE} \tag{16}$$

Where S is maximum intensity and MSE is the mean square error. A higher value of PSNR means the de-noised image is of good quality and is close to reference image.

Mean absolute error

It is the average of absolute difference between de-noised image and reference image. It is used to measure how close the de-noised image is to reference image [29]. The MAE is defined as follow.

$$\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|\hat{f}(i,j)-f(i,j)\right| \tag{17}$$

A lower value of MAE means the de-noised image is close to reference image.

Maximum difference

It is used to measure maximum difference between de-noised image and reference image. A large value of MD means de-noised image is of poor quality. In simple words it is used to measure the maximum error [29]. The MD is defined as follow:

$$\max\left|\hat{f}(i,j)-f(i,j)\right| \tag{18}$$

Structural content

It is a ratio between sums of square of intensities of reference image to sum of square of intensities of de-noised image [29]. The value of SC will be close to 1 for good quality image. The SC is defined as follow:

$$\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(f(i,j))^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}(\hat{f}(i,j))^2} \tag{19}$$

Normalized absolute error

It is used to find error prediction accuracy of the de-noised image. The SC is defined as follow [29].

$$\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left|\hat{f}(i,j)-f(i,j)\right|}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left|f(i,j)\right|} \tag{20}$$

Normalized cross correlation

It is a correlation function which is used to measure closeness between reference image and de-noised image [29]. It is used to measure similarity, if two images are identical images the value of NK will be 1. The NK is defined as follow

$$\frac{\sum_{i=1}^{M}\sum_{j=1}^{N} f(i,j)) \cdot \hat{f}(i,j)}{\sum_{i=1}^{M}\sum_{j=1}^{N} (f(i,j))^2} \tag{21}$$

Laplacian mean square error

Local contrast is having a crucial role in definition image quality. The LMSE is a method used for evaluating local contrast of image [29]. The LMSE is defined as follow

$$\frac{\sum_{i=1}^{M}\sum_{j=1}^{N} (L(\hat{f}(i,j)) - L(f(i,j)))^2}{\sum_{i=1}^{M}\sum_{j=1}^{N} L(f(i,j))^2} \tag{22}$$

Where

$L(f(i,j)) = f(i+1,j) + f(i-1,j), f(i,j+1) + f(i,j-1) - 4f(i,j)$

and

$L(\hat{f}(i,j)) = \hat{f}(i+1,j) + \hat{f}(i-1,j), \hat{f}(i,j+1) + \hat{f}(i,j-1) - 4\hat{f}(i,j)$

Structural similarity index

It is used to quantify structural changes which include luminance, contrast and texture of digital image. The greater value of SSIM means greater similarity between reference image and de-noised image [30]. The SSIM is defined as follow:

$$\frac{\left(2\mu_f \mu_{\hat{f}} + C_1\right)\cdot\left(2\sigma_{f,\hat{f}} + C_2\right)}{\left(\mu_f^2 + \mu_{\hat{f}}^2 + C_1\right)\cdot\left(\sigma_f^2 + \sigma_{\hat{f}}^2 + C_2\right)} \tag{23}$$

Where μ_f is the mean intensity of reference image, $\mu_{\hat{f}}$ is mean intensity of de-noised image, σ_f^2 is variance of reference image, $\sigma_{\hat{f}}^2$ is variance of de-noised image, $\sigma_{f,\hat{f}}$ is Covariance of reference and de-noised image.

RESULTS AND DISCUSSIONS

The algorithms are compared using experimental evaluation, by adding speckle noise of variance 0.1, Salt & Pepper noise of variance 0.1 and Gaussian noise of mean 0 and variance 0.1 on standard grayscale test image of Lenna of size 512x512 and class uint8 taken from USC-SIPI image database. The quality of filtered image is compared using full reference objective quality measures PSNR, RMSE, AD, SC, NCC, MD, LMSE, NAE and SSIM. The implementation is done on Matlab R2016B (Version 9.1). The noisy image and filtered images obtained by applying various spatial filtering techniques are given in Figures 10, 11 and 12 where Figure-10 shows image corrupted with speckle noise and images filtered using various spatial filtering techniques. Similarly Figures 11 and 12 shows filtering results on image corrupted using salt and pepper noise and image corrupted using Gaussian noise. The values of objective quality metrics on noisy and filtered images are given in Table-1, 2 and 3. Visual comparisons of objective quality metrics on noisy and filtered images are given in Figures 13 to 18 in the form of bar charts.

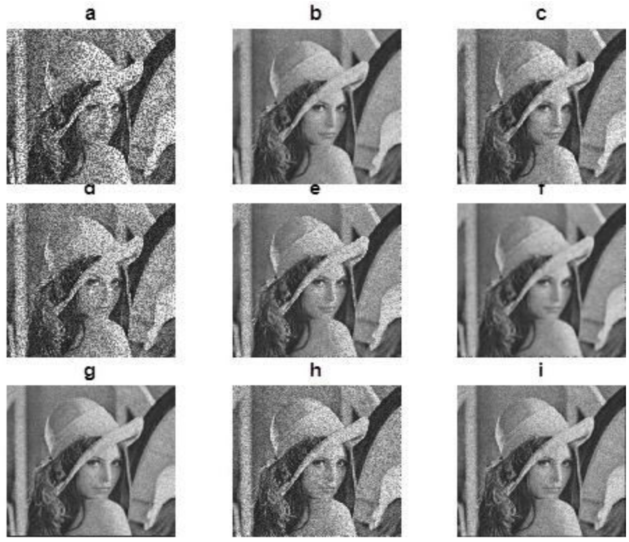

Figure-11. ‘a’ is image corrupted with Speckle noise, ‘b’ is image filtered with Mean filter, ‘c’ is image filtered with Median filter, ‘d’ is image filtered with Adaptive_median filter, ‘e’ is image filtered with Wiener_filter, ‘f’ is image filtered with Lee filter, ‘g’ is image filtered with Kuan filter, ‘h’ is image filtered with Frost filter, ‘i’ is image filtered with Anisotropic_Diffussion filter.

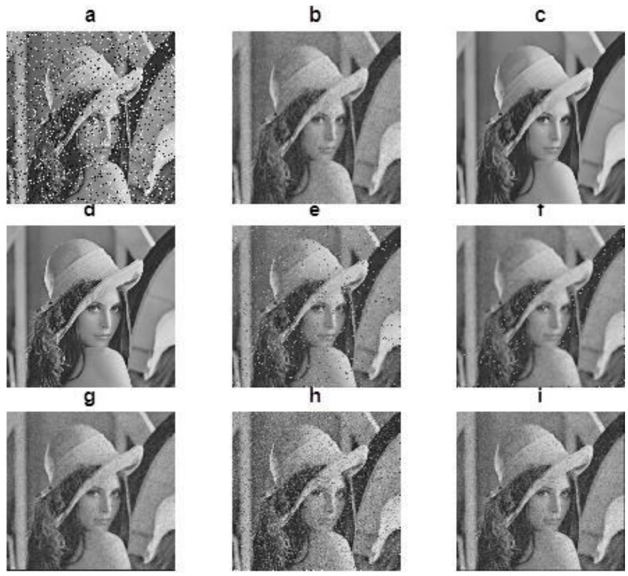

Figure-12. ‘a’ is image corrupted with Salt & Pepper noise, ‘b’ is image using Mean filter, ‘c’ is image using Median filter, ‘d’ is image using AWMF, ‘e’ is image using Wiener_filter, ‘f’ is image using Lee filter, ‘g’ is usingKuan filter, ‘h’ is image using Frost filter, ‘i’ is using Anisotropic filter.

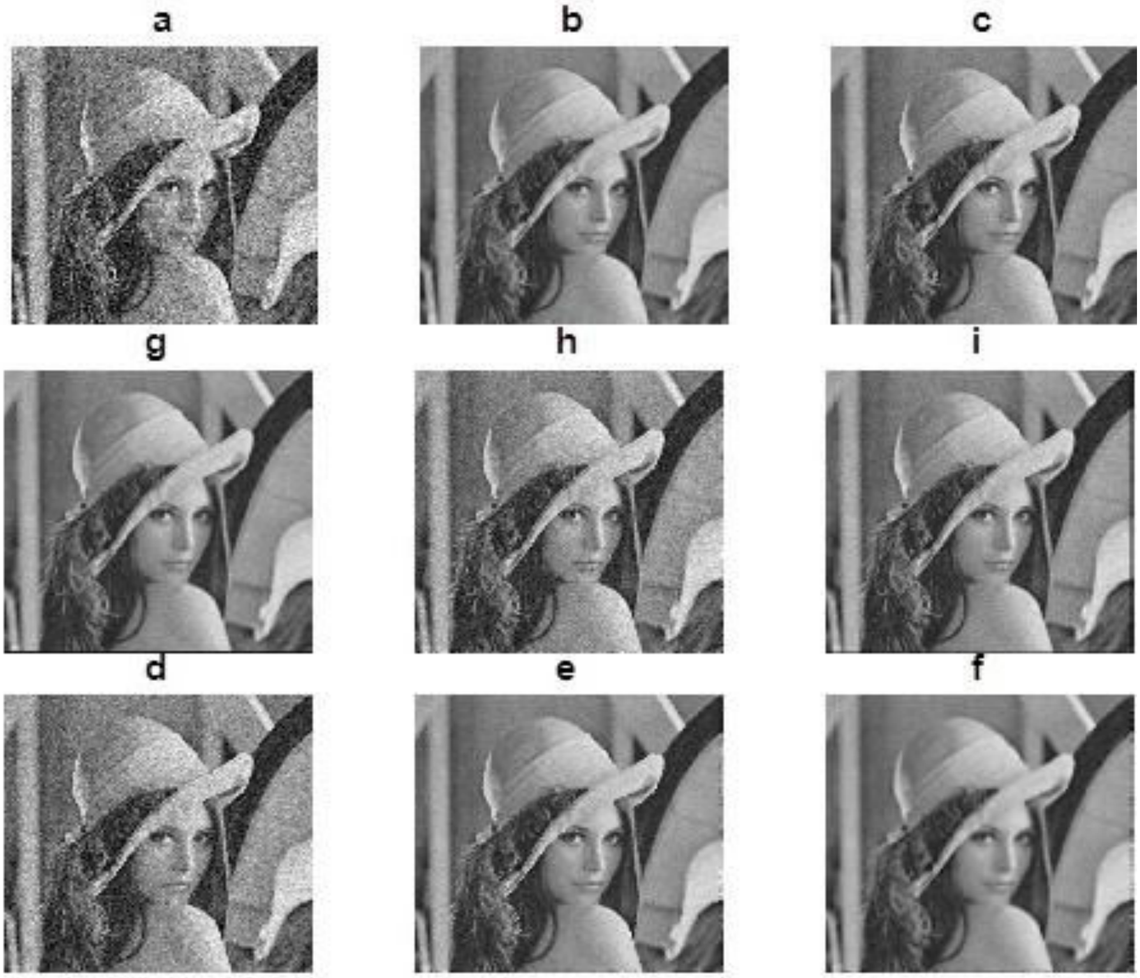

Figure-13. 'a' is image corrupted with Gaussian noise, ''b' is image using Mean filter, 'c' is imageusing Median filter, 'd' is image using AWMF, 'e' is image using Wiener_filter, 'f' is imageusing Lee filter, 'g' is using Kuan filter, 'h' is image using Frost filter, 'i' is usingAnisotropic filter.

Table-1. The values of RMSE, PSNR, AD, SC, NCC, MD, LMSE, NAE and SSIM in the presence of Speckle noise and in images filtered using Mean, Median, AWMF, Wiener, Lee, Kuan, Frost and Anisotropic diffusion filters.

	RMSE	**PSNR**	**AD**	**SC**	**NCC**	**MD**	**LMSE**	**NAE**	**SSIM**
Speckle Noise	40.456	15.991	33.070	0.933	0.990	124.000	82.849	0.267	0.201
Mean	14.769	24.744	11.285	1.015	0.986	89.000	2.433	0.091	0.500
Median	22.194	21.206	17.100	0.988	0.992	115.000	7.648	0.138	0.360
AWMF	31.728	18.102	24.973	0.980	0.982	121.000	40.225	0.201	0.237
Wiener	19.722	22.232	14.644	1.004	0.987	116.000	10.886	0.118	0.434
Lee	11.699	26.768	8.595	1.003	0.981	114.000	0.952	0.069	0.670
Kuan	14.245	25.057	9.235	1.032	0.979	194.000	0.984	0.074	0.663
Frost	21.205	21.602	16.234	0.999	0.988	116.000	27.008	0.131	0.350
Anisotropic	13.521	25.610	9.938	1.009	0.981	114.000	3.000	0.071	0.578

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Table-2. The values of RMSE, PSNR, AD, SC, NCC, MD, LMSE, NAE and SSIM in the presence of Salt & Pepper noise and in images filtered using Mean, Median, AWMF, Wiener, Lee, Kuan, Frost and Anisotropic diffusion filters.

	RMSE	PSNR	AD	SC	NCC	MD	LMSE	NAE	SSIM
Salt&Pepper Noise	42.907	15.480	12.652	0.924	0.989	234.000	91.735	0.102	0.176
Mean	16.146	23.969	11.507	1.013	0.986	108.000	2.644	0.093	0.464
Median	5.202	33.808	2.782	1.003	0.998	195.000	0.869	0.022	0.910
AWMF	3.188	38.060	0.968	1.001	0.999	94.000	0.461	0.008	0.962
Wiener	26.951	19.519	12.985	0.987	0.986	205.000	27.041	0.105	0.312
Lee	16.960	23.542	10.140	1.024	0.980	194.000	5.950	0.082	0.569
Kuan	15.139	24.529	10.027	1.030	0.979	192.000	1.003	0.081	0.644
Frost	22.705	21.008	13.624	0.996	0.988	226.000	29.629	0.110	0.314
Anisotropic	14.682	24.795	10.402	1.027	0.981	122.000	3.226	0.084	0.550

Table-3. The values of RMSE, PSNR, AD, SC, NCC, MD, LMSE, NAE and SSIM in the presence of Gaussian noise and in images filtered using Mean, Median, AWMF, Wiener, Lee, Kuan, Frost and Anisotropic diffusion filters.

	RMSE	PSNR	AD	SC	NCC	MD	LMSE	NAE	SSIM
Gaussian Noise	25.303	20.067	20.257	0.965	1.000	112.000	32.358	0.163	0.265
Mean	9.984	28.145	7.796	1.001	0.997	69.000	1.439	0.063	0.642
Median	11.710	26.760	9.222	0.998	0.997	74.000	2.509	0.074	0.564
AWMF	18.006	23.023	14.242	0.985	0.998	81.000	13.542	0.115	0.368
Wiener	11.257	28.703	8.616	0.999	0.997	80.000	2.899	0.069	0.794
Lee	9.387	28.680	6.588	1.014	0.991	85.000	1.008	0.053	0.759
Kuan	12.331	26.311	7.156	1.013	0.989	189.000	0.962	0.058	0.755
Frost	13.743	25.369	10.898	0.993	0.998	89.000	11.205	0.088	0.467
Anisotropic	10.452	27.747	7.299	1.012	0.991	105.000	1.768	0.059	0.703

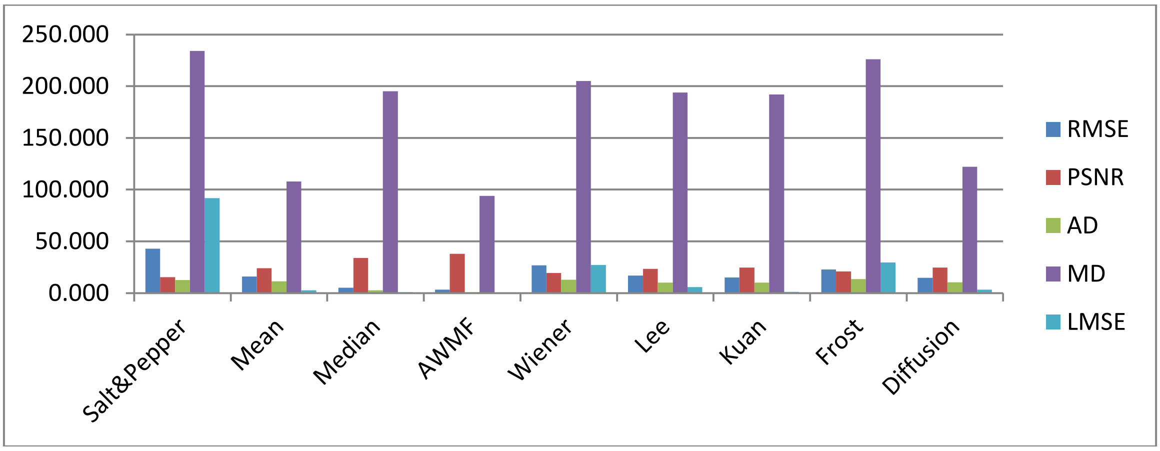

Figure-14. Comparison of RMSE, PSNR, AD, MD and LMSE in the presence of Salt & Pepper noise and in images filtered using Mean, Median, AWMF, Wiener, Lee, Kuan, Frost and Anisotropic diffusion filters.

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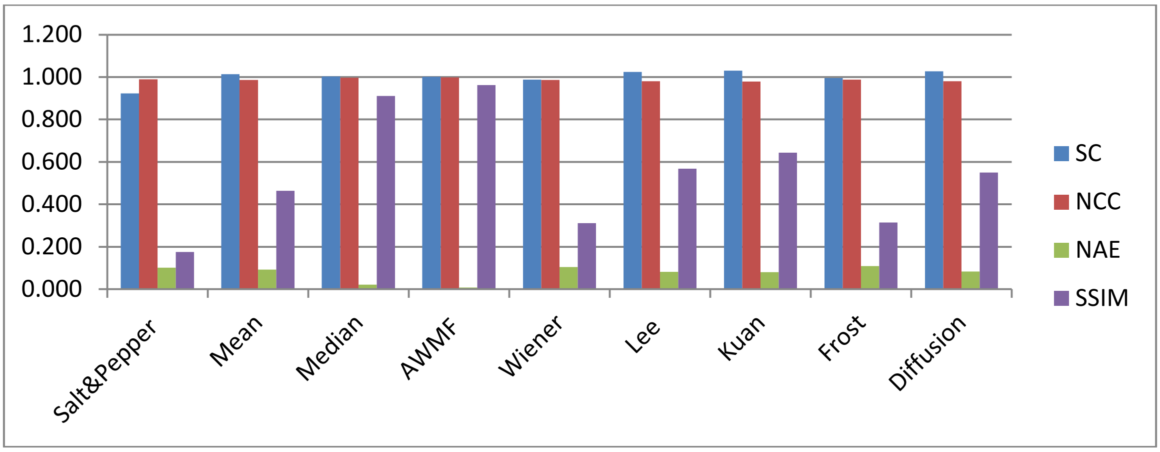

Figure-15. Comparison of SC, NCC, NAE and SSIM in the presence of Salt & Pepper noise and in images filtered using Mean, Median, AWMF, Wiener, Lee, Kuan, Frost and Anisotropic diffusion filters.

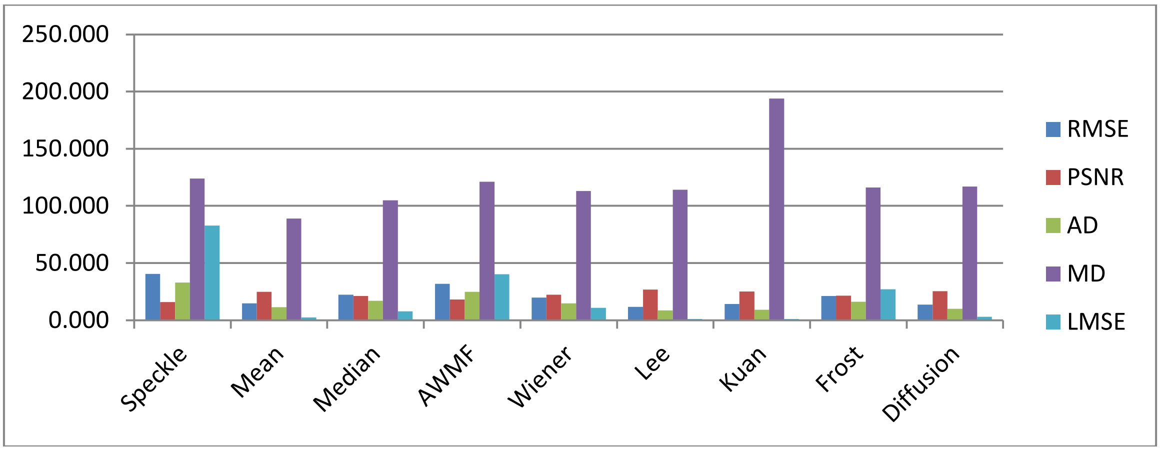

Figure-16. Comparison of RMSE, PSNR, AD, MD and LMSE in the presence of Speckle noise and in images filtered using Mean, Median, AWMF, Wiener, Lee, Kuan, Frost and Anisotropic diffusion filters.

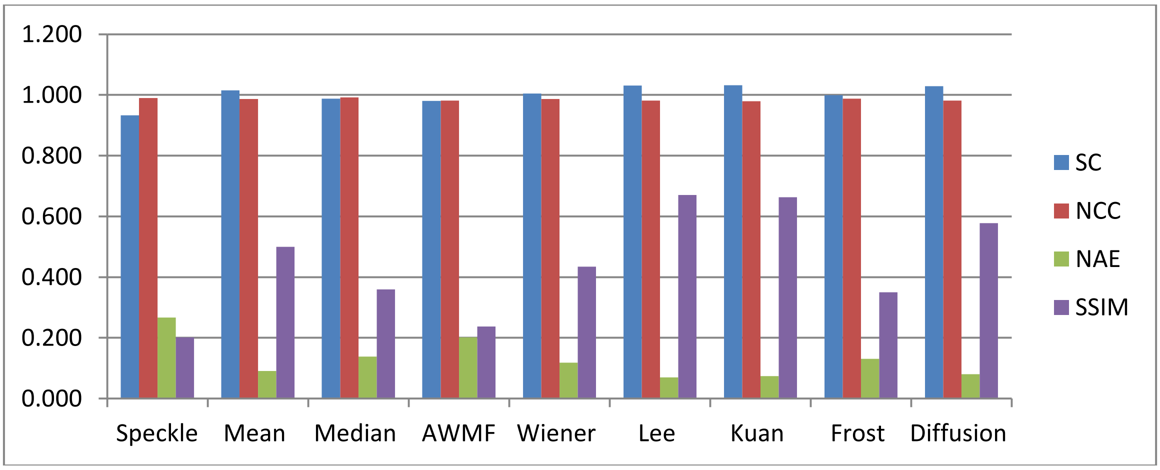

Figure-17. Comparison of SC, NCC, NAE and SSIM in the presence of Speckle noise and in images filtered using Mean, Median, AWMF, Wiener, Lee, Kuan, Frost and Anisotropic diffusion filters.

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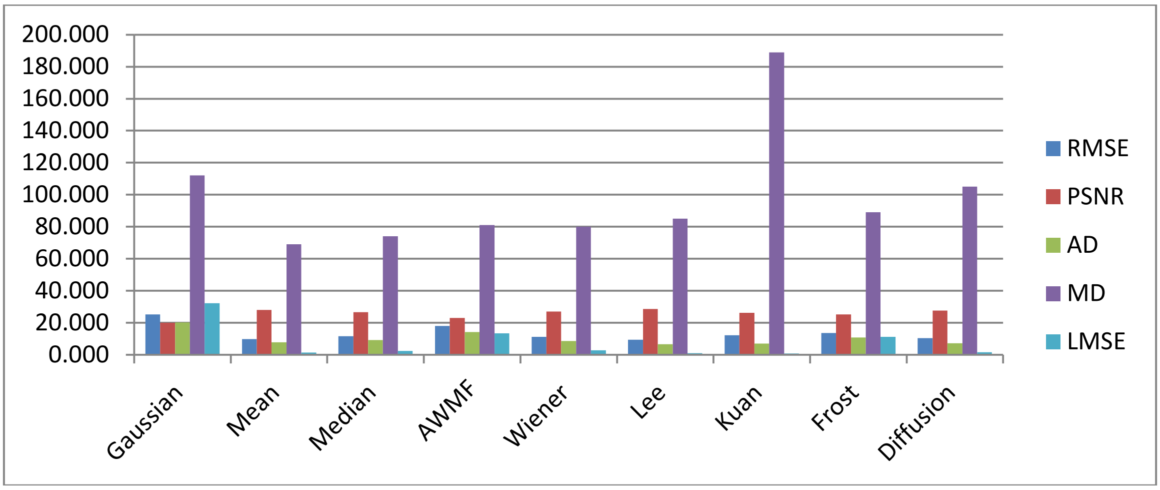

Figure-18. Comparison of RMSE, PSNR, AD, MD and LMSE in the presence of Gaussian noise and in images filtered using Mean, Median, AWMF, Wiener, Lee, Kuan, Frost and Anisotropic diffusion filters.

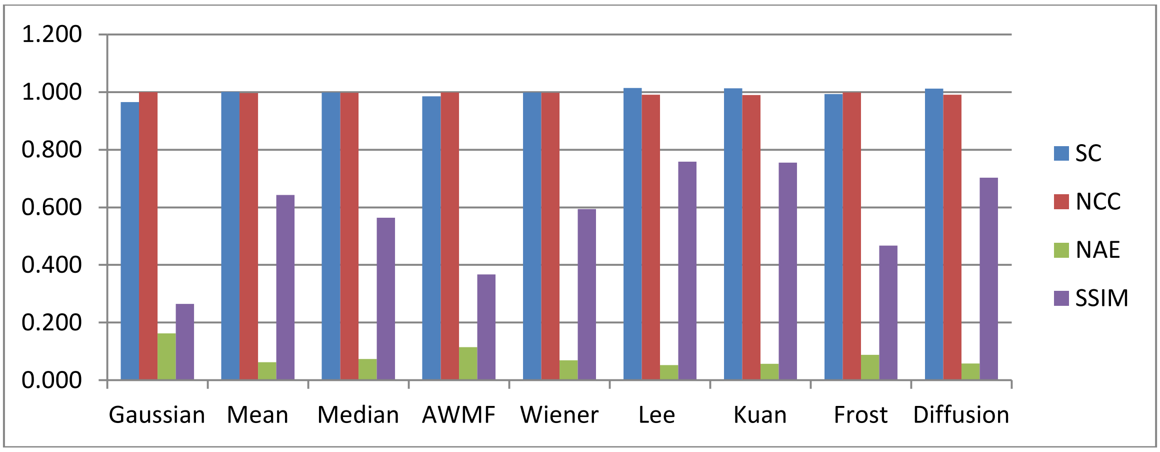

Figure-19. Comparison of SC, NCC, NAE and SSIM in the presence of Gaussian noise and in images filtered using Mean, Median, AWMF, Wiener, Lee, Kuan, Frost and Anisotropic diffusion filters.

CONCLUSIONS

In this paper we have worked on eight different spatial filtering techniques using nine full-reference based image quality metrics. A comparative study of spatial filtering techniques on standard test image of Lenna corrupted of Gaussian, speckle and salt and pepper noise was carried out. We obtained very useful results which depicts that each filter works well for certain type of noise models and does not work so good for other models. The analysis was done using subjective interpretation of filtered images as well as using full reference based image quality metrics. By comparing the results of image quality metrics the conclusion is made that the Speckle noise can be reduced using Lee, Kuan and Anisotropic diffusion filter, Salt and Pepper noise can be suppressed using Median and AWMF and for Gaussian noise mean and wiener filter are immensely efficient. Although we got good results but still there is a scope of improvement in SSIM in the presence of speckle noise. One of the main future directions is to apply transform filtering in wavelet domain on images corrupted by speckle noise.

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